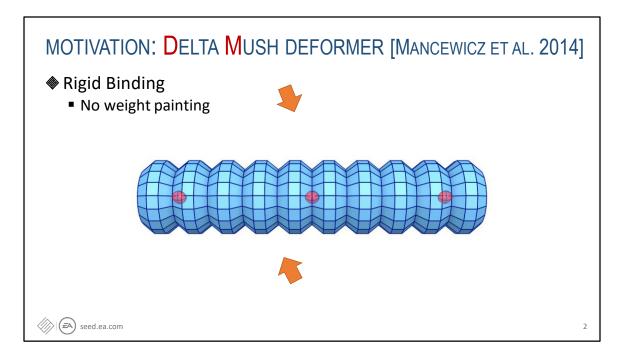


(*) JP Lewis was with SEED//Electronic Arts when we worked on this project.



So firstly to setup the background, I will talk about Delta Mush.

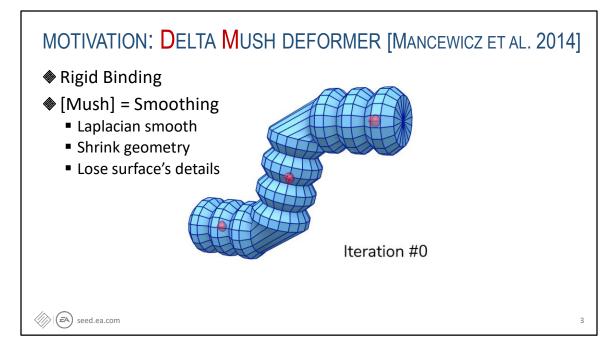
It is a quite popular tool in industry.

The idea is to reduce the authoring cost by avoiding weight-painting.

For example, if we have 3 joints, drawn in red color here,

[click]

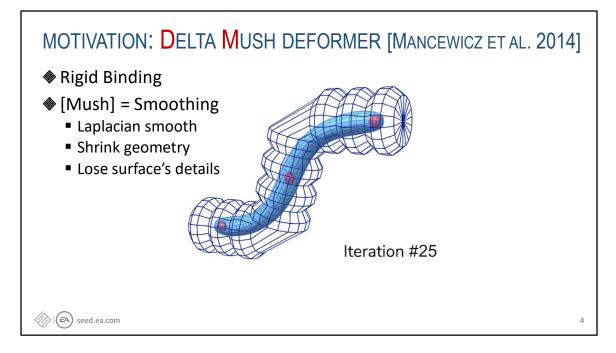
And we will just do the rigid bind, the geometry will break when we animate the joints.



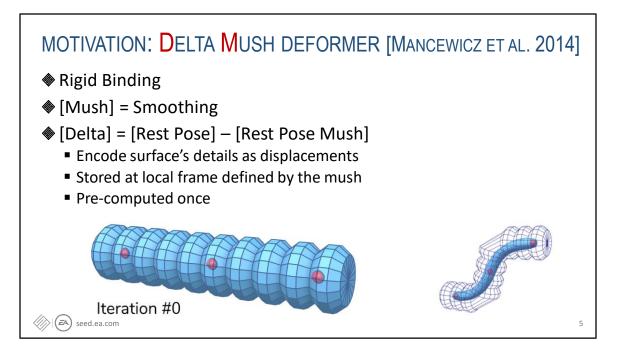
To fix this, Delta Mush uses Laplacian smoothing, or "mushing" as named by the original authors.

[next]

Smoothing fixed broken geometry, but it shrinks the mesh and blurs all details.



[Transition slide: Just leave move to the side]



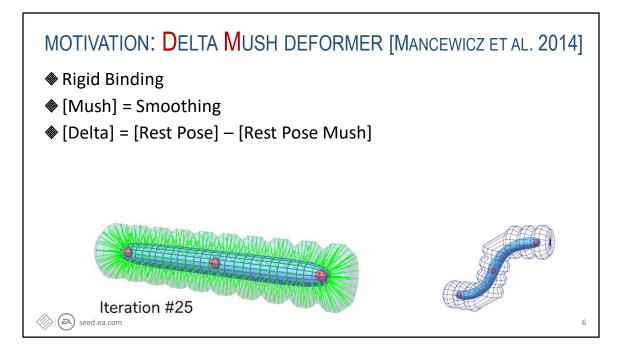
To recover the details, we compute the "Delta",

[next]

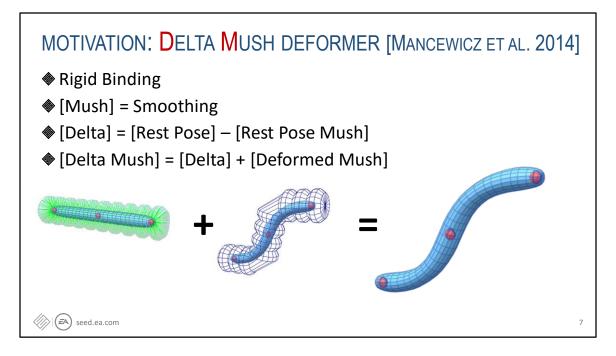
it is the difference in the rest pose between the original geometry and the smooth version stored in the local coordinate frame,

those are green lines in this figure.

And note that we only need to compute the "Delta" once per model, but not at runtime.



So now we will use the Delta to recover the surface's details of the mush.



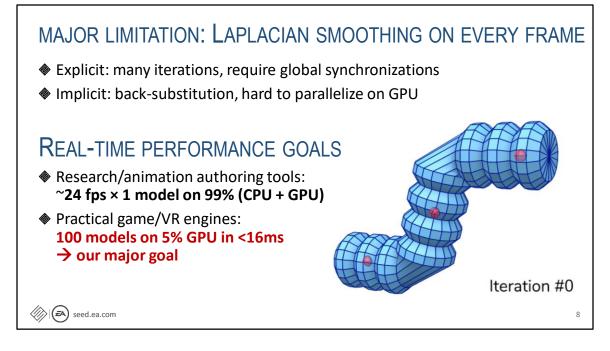
[next]

when we add the Delta on top the Mush using the local coordinate frame of the deformed mush,

[next]

we have the result with smooth deformation and sharp geometry details.

The great thing about Delta Mush is it produces good quality deformation with very simple concept and setup.



But in term of computational complexity, it is not so nice.

The Laplacian smoothing is an iterative algorithm.

For each animation frame, many iterations need to run sequentially with synchronizations in between them.

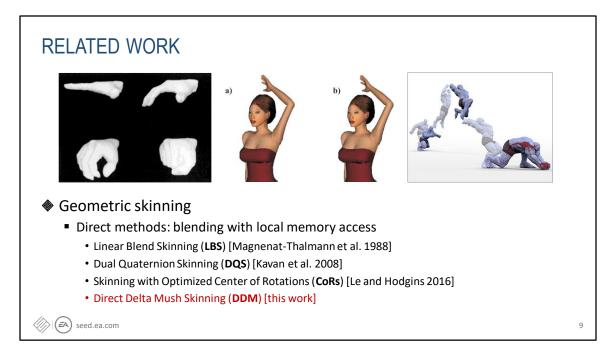
Using implicit Laplacian can reduce the number of iterations

But the trade off is each iteration need to solve large scale linear system. And even with pre-factorization, the back-substitution step is hard to parallel on GPU.

So even Delta Mush can easily reach the real-time performance for small scale research and authoring tools,

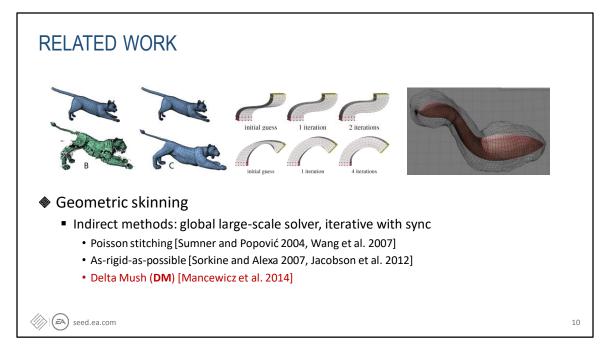
it is not suitable for large scale and high-performance game and VR engines.

And our goal for this project is to make Delta Mush to be a direct skinning method.

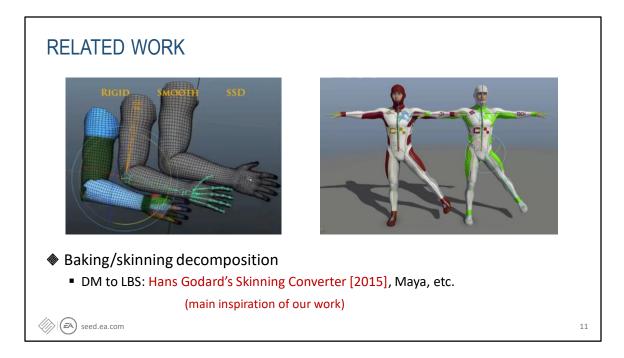


And here is a quick review of the landscape.

Our work shares the similar computing architecture with other direct methods, which typically can compute all vertex transformations in parallel and the computation on each vertex only need to access small local memory. This is suitable for implementation on GPU shaders.



Indirect methods can optimize some global energy term so they typically offer higher quality. But the computation costs are more costly, either with a large-scale linear solver like Poison stitching, or with many iterations and synchronizations like ARAP or DM.

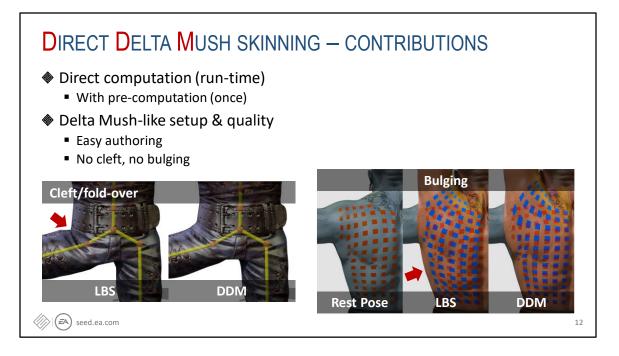


It's also worth to mention that in industry, there is a practice of learning LBS skinning weights from example poses, which is a data fitting problem.

Example poses may be modeled by artist or generated by simulation.

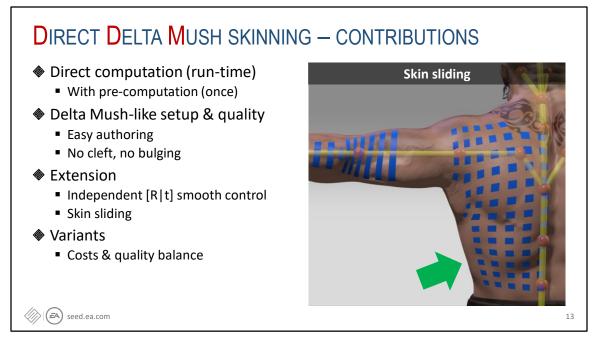
And there was also an idea of using DM to generate example poses.

That was nice because DM is easy to setup, but would be nicer if we don't even need to do data fitting.



With that inspiration, we reworked the math and made a direct model that respects all the goods of the original Delta Mush,

which means high quality deformation with no weight painting.

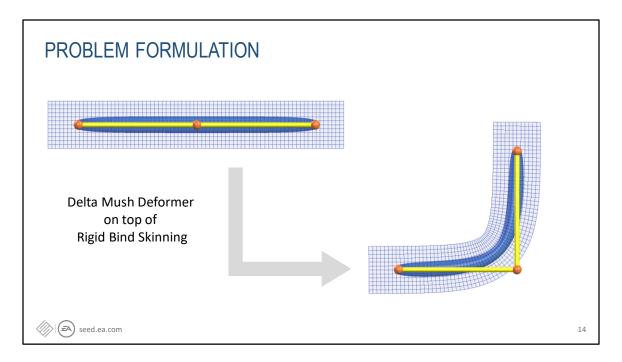


We even extended the original model to improve the quality.

Here we show the skin sliding effect produced by setting different smoothness amounts of rotation and translation.

To our knowledge, this is the first direct model can do skin sliding. [click]

And finally, we offer different variants to balance computing, storage costs and deformation quality



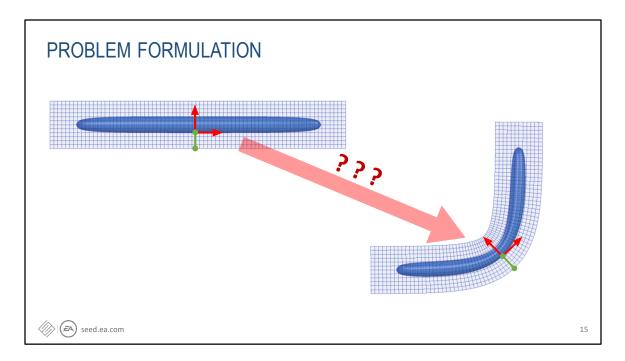
Now I will present the main idea of our model.

Suppose that we deform a bar using Delta Mush where the top left figure here shows the rest pose and the bottom right shows the deformed pose.

The bold blue at the core of each bar shows the corresponding mush.

And the deformation is driven by two rigid bones shown in yellow.

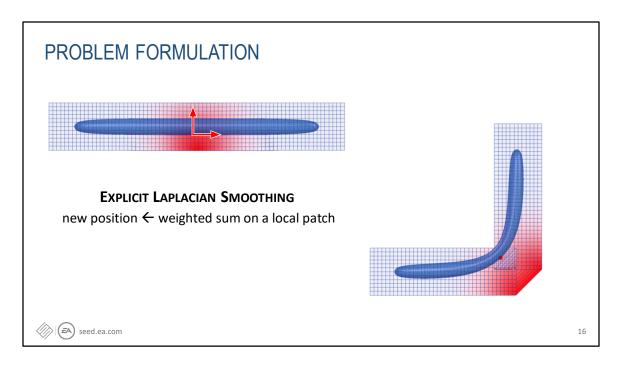
Our setup here is delta mush on top of rigid binding.



For each vertex, Delta Mush needs to define a local coordinate frame to store the delta.

So if I visualize the local frame by red arrows. and the delta in green here should be invariant in the red local frame.

And that means the local transformation to deform the mush, which is this [Click] is also the local transformation to deform the final geometry, which is this [Click]



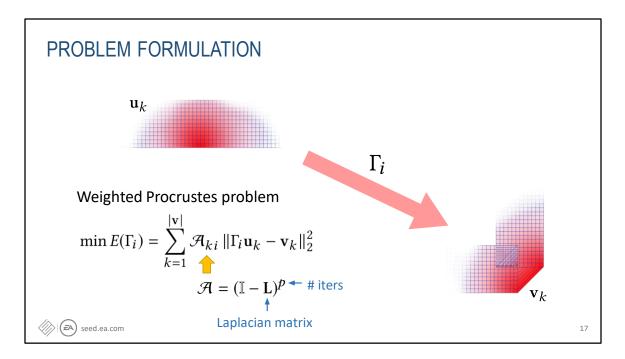
To solve for the vertex transformation of the mush, we realize that when doing Laplacian smoothing,

the final position of each vertex will be the weighted sum of original vertices on a local patch.

In this figure, we show the patch in red with the smooth fall off represent the weights.

And again, we are trying to find this transformation. [click] That will be the same as this transformation of the whole patch.

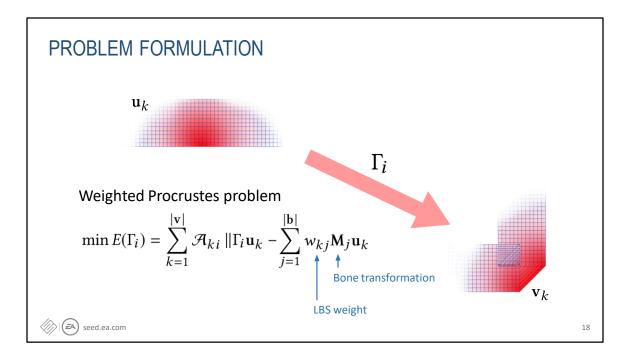
[click]



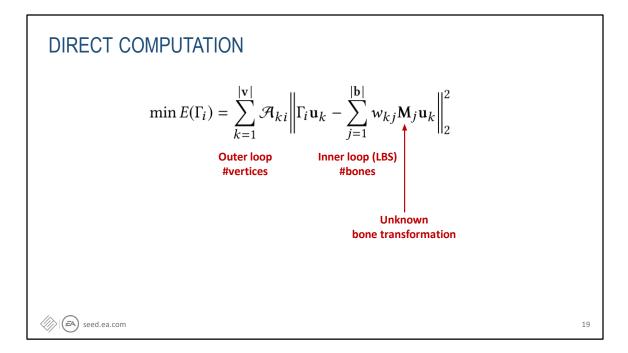
This is a weighted Procrustes problem where we find the best rigid transformation by minimizing the sum of squared differences between two set vertices with applying transformation on one set.

In this formulation, the weights of the local patch A sub ki here is defined by the Laplacian matrix L applying p times.

And I is the identity matrix.



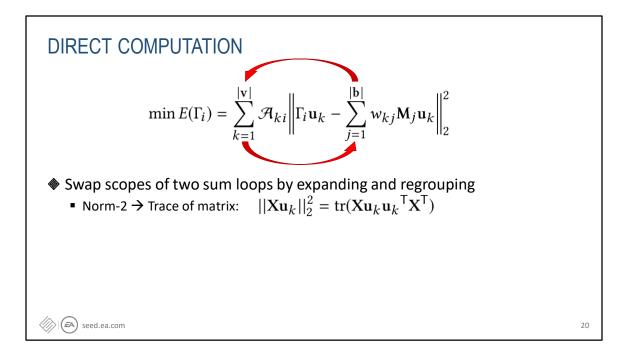
We can rewrite the objective function by replacing the articulated pose by the Linear blend skinning formula where we can use 0/1 skinning weights.



The objective function has two nested sums, you can think of when computing it, you need two nested for loops:

- The outer loop iterates thru all vertices
- And the inner loop iterates thru all bone transformations.

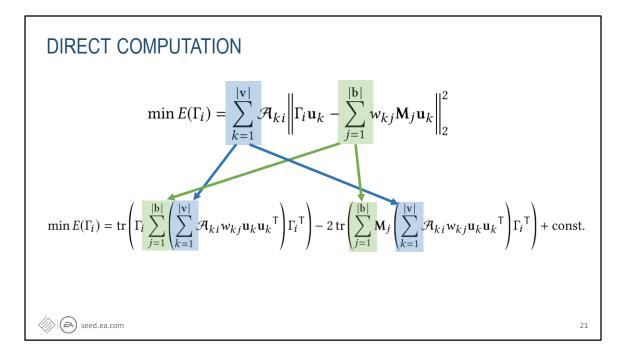
At the inner loop, the bone transformations are unknown before animation, so with traditional Delta Mush, we need to compute this loop for every frame at runtime.



Instead of doing that, we try to rewrite this expression so that we can swap scopes of two sum loops.

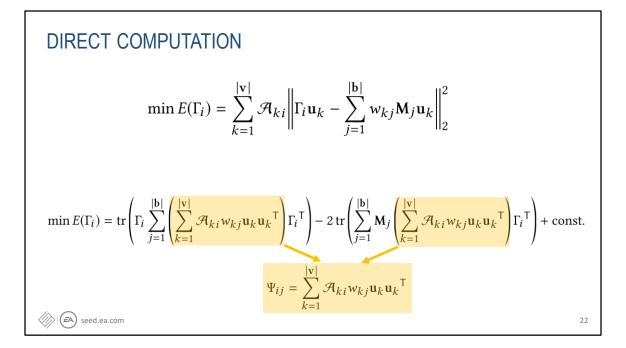
We expand the nested sums and regrouping the terms by the bone transformation M sub j,

Here we use a small trick of rewriting the norm 2 by the trace of the matrix.



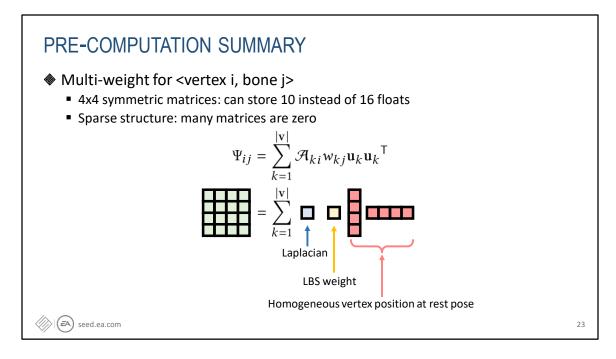
With expanding and regrouping here is what we ended up with. Now the two sum loops have been swapped.

(please don't read the equations, just look at the color blocks).



Another thing you might notice is that by regrouping the sums, now these two inner sum loops are the same and their values are constant regardless of all bone transformations.

That means we can precompute and cache these.



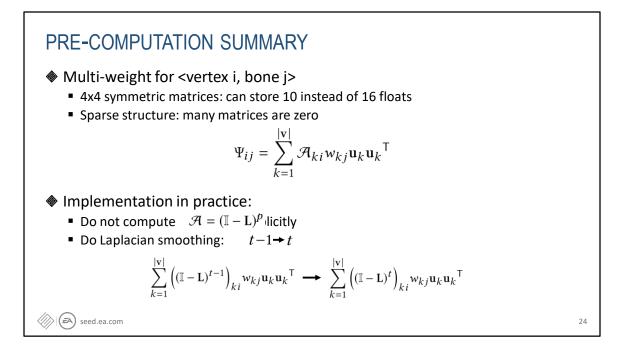
Semantically, we found that the terms we precomputed are similar to multi weights. We denote Psi sub ij as the weight to relate vertex i and bone j.

At the bottom here is the visualization of how they are formed. The Laplacian weight A sub ki and the LBS weight w sub kj here are scalars.

So the final matrix Psi are weighted sum of all outer products u times u transpose. And those outer products are symmetric matrices.

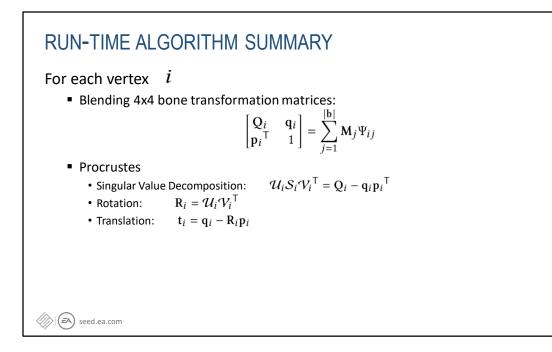
Therefor Psi are also symmetric, and we can save some storage.

We also note that the sparseness structure of these multi weights are also very similar to the regular scalar skinning weights. That means there will be many zero multi weight matrices.



And we also note that in practice, we don't need to compute the matrix A here explicitly, this is a square matrix with size of number of vertices and not so sparse so computing it would be very expensive.

Instead, we do Laplacian smoothing to raise the exponential p one by one. Which means we use the Psi matrices at p = t-1 to compute new Psi matrices at p = t. This is equivalent to do Laplacian smoothing on these Psi matrices with some matrix reshaping.



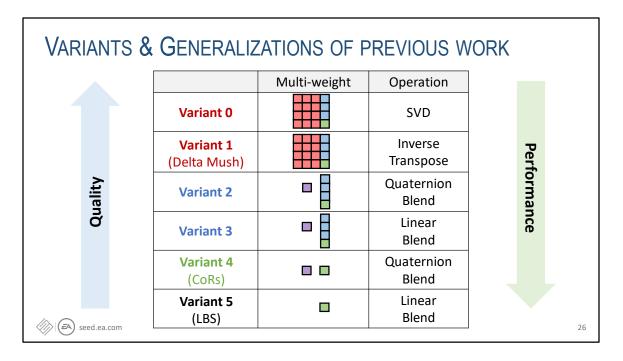
And once we have the pre-computed multi-weight matrices Psi, the run-time algorithm is strait forward.

We need to blend input bone transformation matrices M sub j with weights Psi sub ij. The result is one 4x4 matrix and we can use its sub-blocks Q and p here to solve the Procrustes problem.

Here we use SVD to solve for the rotation matrix R sub i and then use rotation to compute translation vector t sub i.

This algorithm will give the highest deformation quality, however, it could be a bit expensive depending on the implementation of 4x4 matrix operators and the 3x3 SVD.

25



So, we propose some variants of the algorithm to cut some corners and improve the performance.

Here, variant 0 is the original SVD algorithm in the previous slide.

Variant 1 uses inverse transpose to approximate the closet rotation. This is similar to the way of transforming normal vector with LBS.

Variant 2 and 3 reduce the data storage and computation by using one scalar to represent the rotation (which is illustrated by a purple square). Instead of solving for the rotation, we just do rotation blending with this purple scalar weight. and we can either use quaternion (which is variant 2) or linear blending, which is variant 3. Variant 4 further reduce the number of multi weight to 2 and variant 5 just use scalar weight.

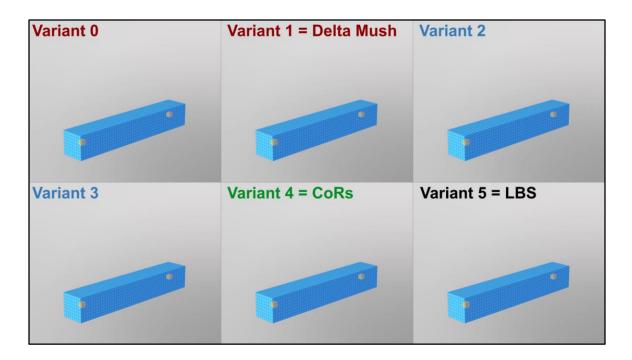
[click]

Some variants are equivalent to previous skinning algorithms:

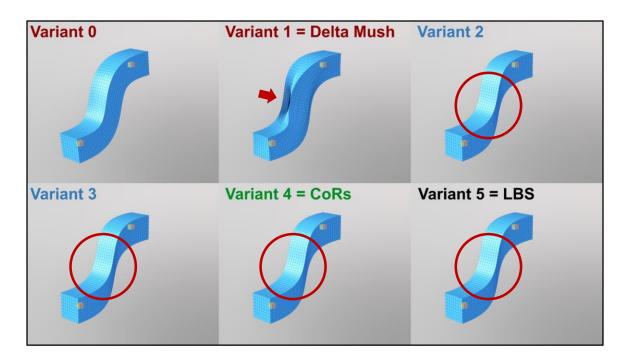
Variant 1 produces exactly the same result as the original Delta Mush, in which the local coordinate frame is represented by two tangent vectors.

Variant 4 here gives the explicit formula to compute the center of rotation for each vertex, which is equivalent to my SIGGRAPH 2016 paper.

And Variant 5 is the same as baking original Delta Mush to Linear Blend Skinning using skinning decomposition.



Here is an example to compare the deformation quality between different variants.



Now I will go back to some poses.

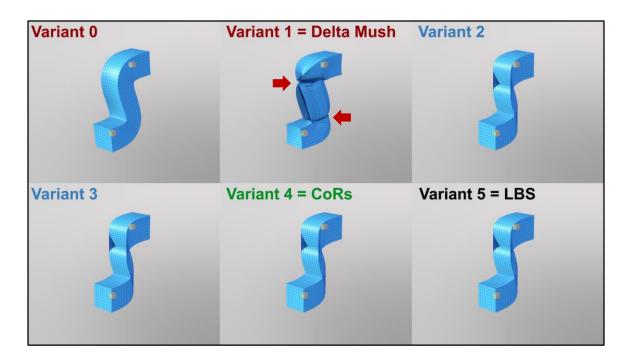
V1 /DM use inv trans, so there is distortion.

Note that in this pose, we only translate but not rotate the joint, so only v0 and v1, which use full 16 multi-weight can propagate this translate into local rotation.

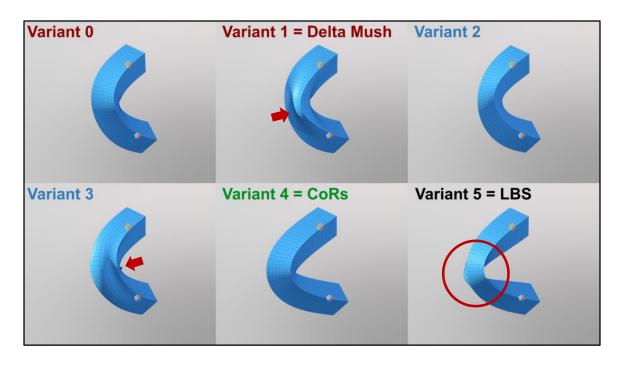
V0 here show nice result, just like many indirect deformers like ARAP.

[click]

But remember than starting from v2, we only use 1 scalar for rotation part, so change in bone translations cannot propagate to the rotation part.

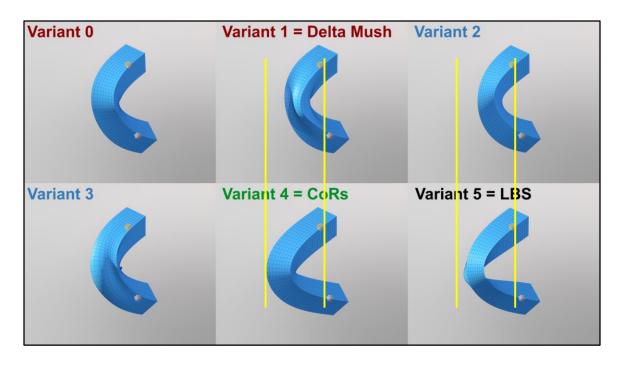


If we lift the joint further, some local transformation of v1 will be inverted.

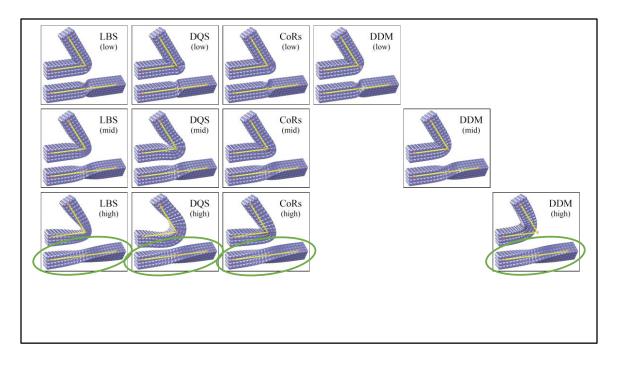


However, in practice, normally we control both rotation and translations. So the difference is less noticeable between variants.

In this case we still see some distortion of v1 here [click] and v3. [click] We also notice that v5, which is LBS collapse here [click], that is the candy wrapper artifact.



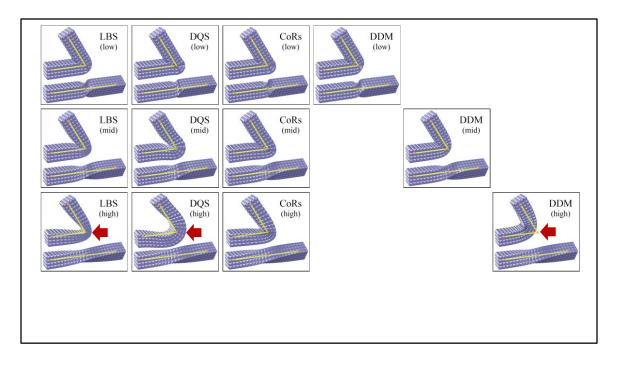
Another thing I want to point out is although the input bone transformations are the same, the profile that different variants bend the bar are different. In this case there might be no explicit right or wrong solution but would be nice if we can have a control over that.



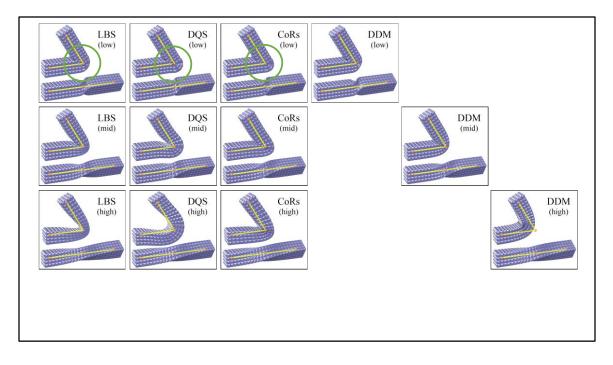
So we introduced an extension for that type of control.

Here is an example of bending and twisting a bar with different level of smoothness. They are setup either by changing the skinning weights diffusions or tuning the number of Laplacian iterations with DDM.

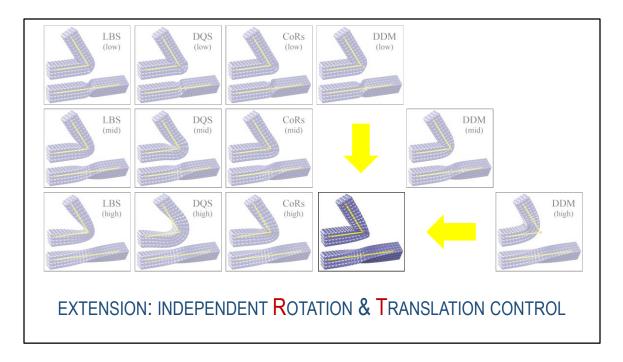
We can see the bar twisted quite nicely with high smoothness, just like the skin sliding we have when twisting the arm.



However, the bending is not good. You can think of it doesn't look like the silhouette of the bent.

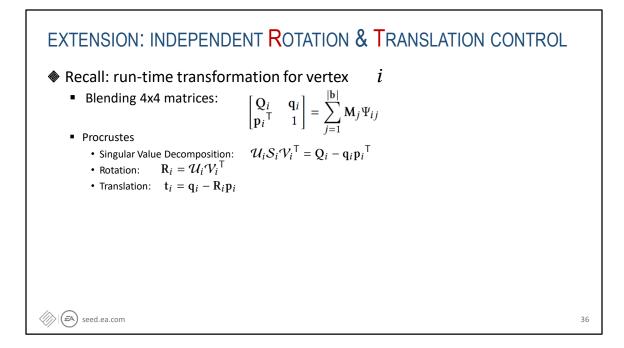


Indeed lower smoothness looks better.

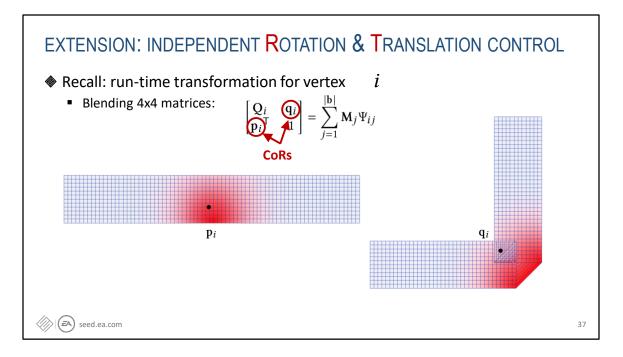


So to bring the best of both, we extend our model to combine two different results as you can see here.

The twisting is smooth while the bending is rigid and looks more like an elbow. This kind of behavior is not possible with previous methods, even with traditional Delta Mush.

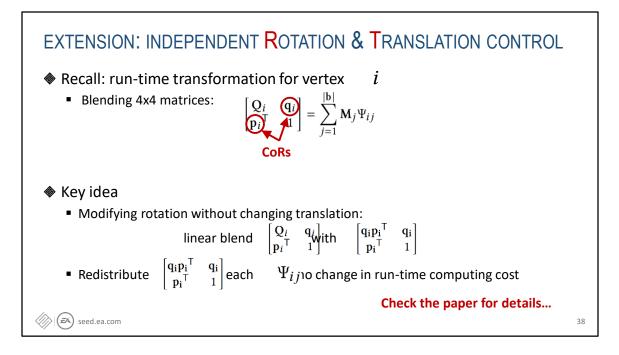


We can do that with no extra cost at runtime. Let's revisit the algorithm here.



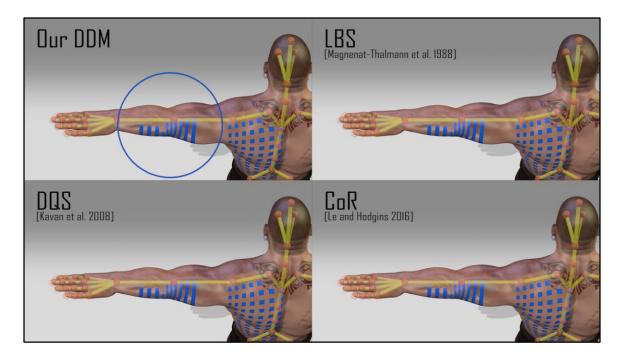
We found after blending transformations to get the 4x4 matrix, these two sub-blocks of the matrix are center of rotations of the Laplacian local patch.

p sub i corresponds to the rest pose and q sub i corresponds to the articulated pose.



So if we use this q times p transpose to construct a new 3x3 sub matrix and blend it to the original, we can change the rotation matrix without changing the translation. Once we have the new matrix, we can redistribute them back to each of the multi weight Psi sub ij, so to the runtime algorithm, the changes will be transparent. And therefore, it does not increase run-time computing cost.

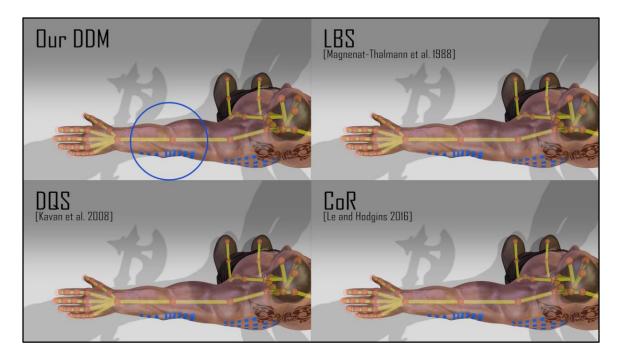
That's the high level idea, please check the paper for more details.



And now is an example of using the extension to setup the skin sliding.

So here you can see the skin does not slide much for other methods such as LBS, DQS, or CoR because of their skinning weights do not diffuse much further from the elbow joint.

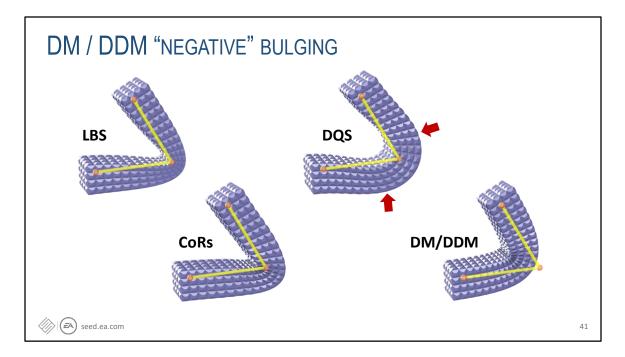
And the reason is artist need to balance between smoothness for twisting and smoothness for bending.



Here is how the deformation looks with bending animation.

You can see that although our DDM has smoother skin sliding on twisting, it has sharper profile on bending, which better represents the inside rigid bone knuckle. And you can still see some skin sliding here.

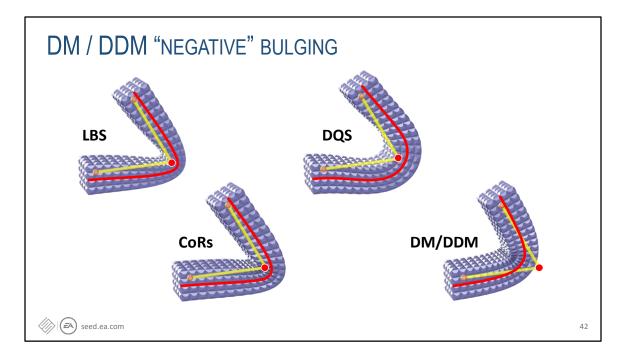
That's all thank to the independent rotation and translation control.



Another property that the independent control supports well for Delta Mush is to utilize the effect we called negative bulging.

[click]

So you might all familiar with the bulging artifact, noticeable with DQS. And actually LBS and Optimized CoRs skinning also have bulging issue.



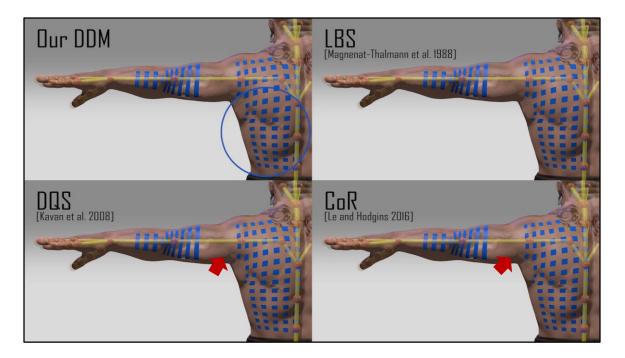
It is more noticeable if we draw the centerline of the side surface.

You can see the pattern here with previous skinning methods is the centerlines budge out of angle limited by two bones.

Only DM and DDM have this centerline curve inside.



This property is useful for the hip joint derformation here. Normally, artist need to put corrective shapes on top of traditional skinning models like LBS or DQS to achieve the same effect.



Here is the last example, I show skin sliding on the back.

Other methods, cannot have skin movement in this region because painting skinning weight of the arm down to this region will lead to more bulging.

You can see that even with influence of the arm stops very close to the shoulder, DQS and optimized CoR skinning still suffer with bulging.

RECAP: DIRECT DELTA MUSH SKINNING AND VARIANTS	
 High performance, GPU friendly, direct geometry skinning model Delta Mush-like setup, no bone-vertex weights required High quality deformation: no bulging, skin sliding 	
Limitations: no collision, no volume preservation, no secondary effect	
 Future work: a call for the community Game engine implementation: data pipeline, 3x3 SVD on GPU Authoring tools: interactive update for precomputation 	
seed.ea.com	45

And to recap, we have made Delta Mush be a direct skinning model, which is suitable for high performance graphics.

We also did some extensions to further improve the deformation quality compared to the original DM model.

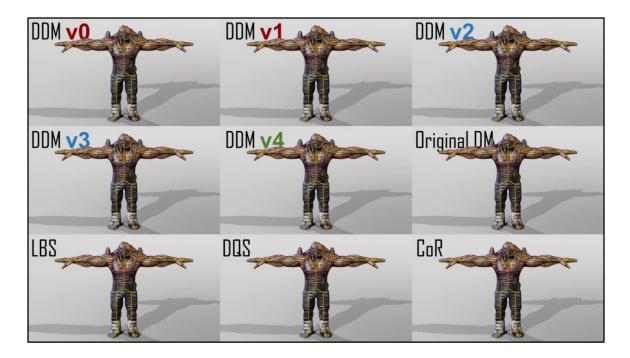
Specially, our model is the first direct method with no bulging and support skin sliding.

However, we have not solved many other problems such as collision, volume preservation, or secondary deformation effect.

We hope that this work can provide theoretical ground and inspiration for the community to further explore this direction. Especially for those who use and love Delta Mush.



To learn more details about this paper: http://binh.graphics/ Questions and comments could be addressed to the first author: bbinh85@gmail.com



Comparison on test animation sequence.

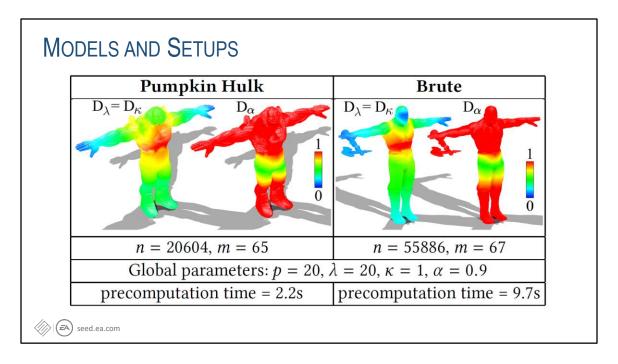


Table 2. The test models, parameters, and pre-computation time of our method. Test models are shown at their rest pose with color coded smoothing weights. n denotes the number of vertices, m denotes the number of bones. Per-vertex smoothing weights $D\lambda$ and $D\kappa$ are set proportional to the distance from the vertex to the bone to approximately represent the radius of each body part. Per-vertex blending weights $D\alpha$ of vertices on the hip area are set to lower values than on other vertices.

CPU PERFORMANCE (SINGLE CORE)											
		v0	v1	v 2	v 3	v 4	v 5				
	Pumpkin Hulk	5.5	4.7	7.1	7.3	5.9	3.3				
	Brute	3.2	2.3	2.9	3.2	2.6	1.6				
Runtime performance comparison between variants. Numbers in this table show the average time to deform one vertex. Time is measured in microseconds on a single-threaded CPU. v5 is equivalent to LBS.											
seed.ea.com										49	

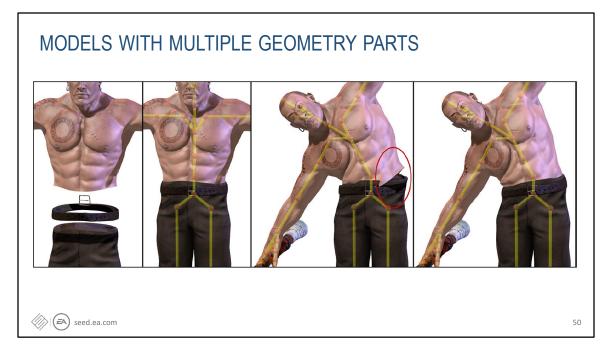


Fig. 6. Our trivial solution to handle models with multiple geometry parts. From left to right: (1) visualization of multiple parts of our character model, (2) the model at rest pose, (3) applying per-part mesh Laplacians breaks the deformation at boundaries of parts, (4) our fix by adding entries to the Laplacian matrix connecting close vertices associated to the same bone.

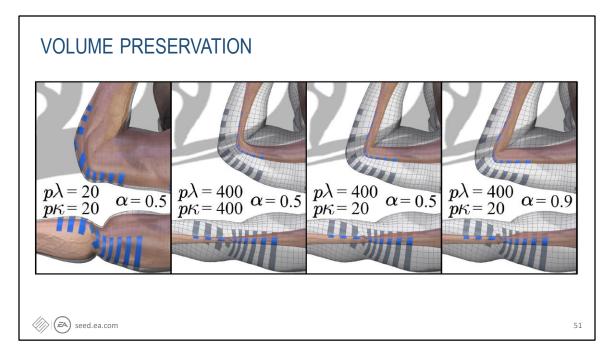


Fig. 11. Volume preservation behavior of the model (gray wireframed) depends on the volume of the mush (color shaded) at the rest pose. Leftmost: with low smoothness $p\lambda$, the mush does not shrink much, but some of this remaining volume can be lost with deformation. Middle and right: with high smoothness $p\lambda$, the mush shrinks to a rod-like shape with near zero volume and this cannot be further reduced by deformation. Bending deformation can be controlled by changing the translation smoothness $p\kappa$ and its blending weight α .